

APPROXIMATING COARSE RICCI CURVATURE ON METRIC MEASURE SPACES WITH APPLICATIONS TO SUBMANIFOLDS OF EUCLIDEAN SPACE

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ABSTRACT. For a submanifold

$$\Sigma \subset \mathbb{R}^N$$

Belkin and Niyogi showed that one can approximate the Laplacian operator using heat kernels. Using a definition of coarse Ricci curvature derived by iterating Laplacians, we approximate the coarse Ricci curvature of submanifolds Σ in the same way. More generally, on any metric measure space we are able to approximate a 1-parameter family of coarse Ricci functions that include the coarse Bakry-Emery Ricci curvature.

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1. INTRODUCTION

In [BN08], Belkin and Niyogi show that the graph Laplacian of a point cloud of data samples taken from a submanifold in Euclidean space converges to the Laplace-Beltrami operator on the underlying manifold. (See also [HAvL05].) Our goal in this paper is to demonstrate that this process can be continued to approximate Ricci curvature as well. This answers a question of Singer and Wu [SW12, pg. 1103], in principle allowing one to approximate the Hodge Laplacian on 1-forms. The Hodge

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Laplacian allows one to extract certain topological information, thus we expect our result to have applications to manifold learning.

To do this, we need to use a modified notion of coarse Ricci curvature defined in [AWb]. Coarse Ricci curvature is a quantity that is derived from a Laplace-type operator and defined on pairs of points rather than tangent vectors, thus it can be defined on any metric measure space. We define a family of coarse Ricci curvature operators which depend on a scale parameter t . We show that when taken on a smooth manifold embedded in Euclidean space, these operators converge to the corresponding smooth Ricci curvature operators as $t \rightarrow 0$.

Our goal is to reconstruct the Ricci using the distance function on the ambient space, and approximation of the Laplacian. A problem arises in that the ambient distance squared function manifests an error at fourth order, see [BN08, Lemma 4.3] Because the definition in [AWb] requires five derivatives to recover Ricci tensor, we have to modify this to a quantity that recovers the tensor using only three derivatives.

More specifically, by iterating the approximate Laplacian operators in [BN08] one can construct an approximate Γ_2 operator, and test this operator on a set of “linear” functions. This defines a coarse Ricci curvature on any two points from a submanifold. This approach recovers the Ric_∞ tensor and can be modified to recover the standard Ricci curvature as well, provided the volume density is smooth.

In this paper we accomplish two things. First, following [BN08] we define a coarse Ricci operator at scale t on any metric measure space. Second, we show that these converge as $t \rightarrow 0$ when taken on a fixed smooth submanifold to the intrinsic coarse Ricci. In [AWa] we show there exists an explicit choice of scales $t_n \rightarrow 0$ such that the quantities converge *almost surely* when computed from a set of n points sampled from a smooth probability distribution on the manifold.

1.1. Background and Motivation. The motivation for the paper stems from both the theory of Ricci lower bounds on metric measure spaces and the theory of manifold learning. For background on the definition coarse Ricci and relation to Ricci curvature lower bounds, see [AWb].

1.1.1. The Manifold Learning Problem. Roughly speaking, the manifold learning problem deals with inferring or predicting geometric information from a manifold if one is only given a point cloud on the manifold, i.e., a sample of points drawn from the manifold at random according to a certain distribution, without any further information. It is clear then that the manifold learning problem is highly relevant to machine learning and to the theory of pattern recognition. An example of an object related to the geometry of an embedded submanifold Σ of Euclidean space that one can “learn” or estimate from a point cloud is the *rough Laplacian* or Laplace-Beltrami operator. Given an embedding $F : \Sigma^d \rightarrow \mathbb{R}^N$ consider its induced metric g . By the rough Laplacian of g we mean the operator defined on functions by $\Delta_g f = g^{ij} \nabla_i \nabla_j f$ where ∇ is the Levi-Civita connection of g . Belkin and Niyogi showed in [BN08] that given a uniformly distributed point cloud on Σ there is a 1-parameter family of operators L_t , which converge to the Laplace-Beltrami operator Δ_g on the submanifold. More precisely, the construction of the operators L_t is based on an approximation of the heat

kernel of Δ_g , and in particular the parameter t can be interpreted as a choice of scale. In order to learn the rough Laplacian Δ_g from a point cloud it is necessary to write a sample version of the operators L_t . Then, supposing we have n data points that are independent and identically distributed (abbreviated by i.i.d.) one can choose a scale t_n in such a way that the operators L_{t_n} converge almost surely to the rough Laplacian Δ_g . This step follows essentially from applying a quantitative version of the *law of large numbers*. Thus one can almost surely learn spectral properties of a manifold. While in [BN08] it is assumed that the sample is uniform, it was proved by Coifman and Lafon in [CL06] that if one assumes more generally that the distribution of the data points has a smooth, strictly positive density in Σ , then it is possible to normalize the operators L_t in [BN08] to recover the rough Laplacian. More generally, the results in [CL06] and [SW12] show that it is possible to recover a whole family of operators that include the Fokker-Planck operator and the weighted Laplacian $\Delta_\rho f = \Delta f - \langle \nabla \rho, \nabla f \rangle$ associated to the smooth metric measure space $(M, g, e^{-\rho} d\text{vol})$, where ρ is a smooth function. Since then, Singer and Wu have developed methods for learning the rough Laplacian of an embedded submanifold on 1-forms using *Vector Diffusion Maps* (VDM) (see for example [SW12]). The relationship of Ricci curvature to the Hodge Laplacian on 1-forms is given by the Weitzenböck formula.

In this paper we consider the problem of learning the Ricci curvature of an embedded submanifold Σ of \mathbb{R}^N at a point from a point cloud. The idea is to construct a notion of coarse Ricci curvature that will serve as a sample estimator of the actual Ricci curvature of the embedded submanifold Σ . In order to explain our results we provide more background in the next section.

1.2. Iterated Carré du Champ. Given an operator L we define the Carré du champ as follows.

$$(1.1) \quad \Gamma(L, u, v) = \frac{1}{2} (L(uv) - L(u)v - uL(v)).$$

We will also consider the *iterated Carré du Champ* introduced by Bakry and Emery [BÉ85] denoted by Γ_2 and defined by

$$(1.2) \quad \Gamma_2(L, u, v) = \frac{1}{2} (L(\Gamma(L, u, v)) - \Gamma(L, Lu, v) - \Gamma(L, u, Lv)).$$

When L is the rough Laplacian with respect to the metric g , then

$$\Gamma(\Delta_g, u, v) = \langle \nabla u, \nabla v \rangle.$$

Notation 1.1. When considering the operators (1.1) and (1.2) we will use the slightly cumbersome three-parameter notation, as the main results will be stated in terms of a family of operators $\{L_t\}$.

1.3. Coarse Ricci Curvature. In this section we provide a definition of coarse Ricci curvature on general metric measures spaces, using a family of operators which are intended to approximate a Laplace operator on a space at scale t . The coarse Ricci curvature will then be defined on pairs of points. For submanifolds in Euclidean space,

the obvious choice is the linear function whose gradient is the vector that points from a point x to a point y . On a genereal metric space X , given $x, y \in X$ define

$$f_{x,y}(z) = \frac{1}{2} (d^2(x, y) - d^2(y, z) + d^2(z, x)).$$

Note that in Euclidean space this is

$$(1.3) \quad f_{x,y}(z) = \langle y - x, z \rangle.$$

This leads us to the following definition of coarse Ricci curvature.

Definition 1.2. *Given an operator L we define the coarse Ricci curvature for L as*

$$\text{Ric}_L(x, y) = \Gamma_2(L, f_{x,y}, f_{x,y})(x).$$

We recall the main results from [AWb].

Theorem 1.3. *Let*

$$\Delta_\rho v = \Delta_g v - \langle \nabla \rho, \nabla v \rangle_g$$

be the wieghted Laplacian and let

$$\text{Ric}_\infty = \text{Ric} + \nabla_g^2 \rho$$

Then

$$(1.4) \quad \text{Ric}_\infty(\gamma'(0), \gamma'(0)) = \frac{1}{2} \frac{d^2}{ds^2} \text{Ric}_{\Delta_\rho}(x, \gamma(s)).$$

and

$$(1.5) \quad \text{Ric}_\infty \geq K$$

if and only if

$$\text{Ric}_{\Delta_\rho}(x, y) \geq K d^2(x, y).$$

As mentioned in the introduction, the ambient distance squared function osculates the instrinsic distance squared function only to third order on the diagonal along the submanifold. So the above formula could manifest some error terms. To side-step this, we appeal to the Bochner formula

$$\Gamma_2(f, f) = \text{Ric}(\nabla f, \nabla f) + \|\nabla^2 f\|^2.$$

We note that if we evaluate Γ_2 on functions with vanishing Hessian at a point, we can recover the Ricci curvature exactly. For submanifolds in Euclidean space, we normal the functions (1.3) to linear function whose gradient is the *unit* vector that points from a point x to a point y . In particular, given x, y

$$F_{x,y}(z) = \frac{1}{2} \frac{d^2(y, z) - d^2(x, z) - d^2(x, y)}{d(x, y)}.$$

That is

$$(1.6) \quad F_{x,y}(z) = \left\langle \frac{y - x}{|y - x|}, z \right\rangle.$$

This leads us to the following definition of *life-sized* coarse Ricci curvature.

Definition 1.4. *Given an operator L we define the life-sized coarse Ricci curvature for L as*

$$\text{RIC}_L(x, y) = \Gamma_2(L, F_{x,y}, F_{x,y})(x).$$

As we will see, this also can be used to recover the Ricci curvature, without taking any derivatives.

1.3.1. Approximations of the Laplacian, Carré du Champ and its iterate. We now construct operators which can be thought of as approximations of the Laplacian on metric measure spaces. This construction is a slight modification of the approximation constructed by Belkin-Niyogi in [BN08] and more generally Coifman-Lafon in [CL06]. Consider a metric measure space (X, d, μ) with the Borel σ -algebra such that $\mu(X) < \infty$. Given $t > 0$, let θ_t be given by

$$(1.7) \quad \theta_t(x) = \int_X e^{-\frac{d^2(x,y)}{2t}} d\mu(y).$$

We define a 1-parameter family of operators L_t as follows: given a function f on X define

$$(1.8) \quad L_t f(x) = \frac{2}{t\theta_t(x)} \int_X (f(y) - f(x)) e^{-\frac{d^2(x,y)}{2t}} d\mu(y).$$

With respect to this L_t one can define a Carré du Champ on appropriately integrable functions f, h by

$$(1.9) \quad \Gamma(L_t, f, h) = \frac{1}{2} (L_t(fh) - (L_t f)h - f(L_t h)),$$

which simplifies to

$$(1.10) \quad \Gamma(L_t, f, h)(x) = \frac{1}{t\theta_t(x)} \int_X e^{-\frac{d^2(x,y)}{2t}} (f(y) - f(x))(h(y) - h(x)) d\mu.$$

In a similar fashion we define the iterated Carré du Champ of L_t to be

$$(1.11) \quad \Gamma_2(L_t, f, h) = \frac{1}{2} (L_t(\Gamma(L_t, f, h)) - \Gamma(L_t, L_t f, h) - \Gamma(L_t, f, L_t h)).$$

Remark 1.5. *This definition of L_t differs from Belkin-Niyogi operator in that we normalize by $\theta_t(x)$ instead of $(2\pi t)^{d/2}$ for an assumed manifold dimension d .*

1.4. Statement of Results. We will consider a closed, smooth, embedded submanifold Σ of \mathbb{R}^N , and the metric measure space will be $(\Sigma, \|\cdot\|, d\text{vol})$, where

- $\|\cdot\|$ is the distance function in the ambient space \mathbb{R}^N ,
- $d\text{vol}_\Sigma$ is the volume element corresponding to the metric g induced by the embedding of Σ into \mathbb{R}^N .

In addition we will adopt the following conventions

- All operators L_t , $\Gamma(L_t, \cdot, \cdot)$ and $\Gamma_2(L_t, \cdot, \cdot)$ will be taken with respect to the distance $\|\cdot\|$ and the measure $d\text{vol}_\Sigma$.

The choice of the above metric measure space is consistent with the setting of manifold learning in which no assumption on the geometry of the submanifold Σ is made, in particular, we have no a priori knowledge of the geodesic distance and therefore we can only hope to use the chordal distance as a reasonable approximation for the geodesic distance. We will show that while our construction at a scale t involves only information from the ambient space, the limit as t tends to 0 will recover the life-size coarse Ricci curvature of the submanifold with intrinsic geodesic distance. As pointed out by Belkin-Niyogi [BN08, Lemma 4.3], the chordal and intrinsic distance functions on a smooth submanifold differ first at fourth order near a point, so while much of the analysis is done on submanifolds, the intrinsic geometry will be recovered in the limit. We are able to show the following.

Theorem 1.6. *Let $\Sigma^d \subset \mathbb{R}^N$ be a closed embedded submanifold, let g be the Riemannian metric induced by the embedding, and let $(\Sigma, \|\cdot\|, d\text{vol}_\Sigma)$ be the metric measure space defined with respect to the ambient distance. Then there exists a constant C_1 depending on the geometry of Σ and the function f such that*

$$(1.12) \quad \sup_{x \in \Sigma} |\Gamma_2(\Delta_g, f, f)(x) - \Gamma_2(L_t, f, f)(x)| < C_1(\Sigma, D^5 f) t^{1/2}.$$

Theorem 1.6 will follow from Corollary 2.2 which is proved in Section 2.

Corollary 1.7. *With the hypotheses of Theorem 1.6 we have*

$$\text{Ric}_{\Delta_g}(x, y) = \lim_{t \rightarrow 0} \Gamma_2(L_t, f_{x,y}, f_{x,y})(x).$$

Theorem 1.6 applies to all functions on the manifold. To obtain the life-size Ricci curvature we apply these to $F_{x,y}$ to obtain the following.

Theorem 1.8. *Let $\Sigma^d \subset \mathbb{R}^N$ be a closed embedded submanifold, and let g be the metric induced by the embedding. Let $\gamma(s)$ be a unit speed geodesic in Σ such that $\gamma(0) = x$. There exists constants C_2, C_3 depending on the geometry of Σ such that*

$$|\text{Ric}(\gamma'(0), \gamma'(0)) - \text{RIC}_{L_t}(x, \gamma(s))| \leq C_2 t^{1/2} + C_3 s.$$

This will be proved in section 2.4.

1.4.1. *Smooth Metric Measure Spaces and non-Uniformly Distributed Samples.* Consider a smooth metric measure space $(M, g, e^{-\rho} d\text{vol})$ and let Δ_ρ be the operator

$$\Delta_\rho u = \Delta_g u - \langle \nabla \rho, \nabla u \rangle_g.$$

In [CL06], the authors consider a family of operators L_t^α which converge to $\Delta_{2(1-\alpha)\rho}$. Note that a standard computation (cf [Vil09, Page 384]) gives

$$\Gamma_2(\Delta_{2(1-\alpha)\rho}, f, f) = \frac{1}{2} \Delta_g \|\nabla f\|_g^2 - \langle \nabla \rho, \nabla \Delta_g f \rangle_g + 2(1-\alpha) \nabla_g^2 \rho(\nabla f, \nabla f).$$

We adapt [CL06] to our setting: Recall that

$$(1.13) \quad \theta_t(x) = \int_X e^{-\frac{d^2(x,y)}{2t}} d\mu(y),$$

and define, for $\alpha \in [0, 1]$

$$(1.14) \quad \theta_{t,\alpha}(x) = \int_X e^{-\frac{d^2(x,y)}{2t}} \frac{1}{[\theta_t(y)]^\alpha} d\mu(y).$$

We can define the operator

$$(1.15) \quad L_t^\alpha f(x) = \frac{2}{t} \frac{1}{\theta_{t,\alpha}(x)} \int e^{-\frac{d^2(x,y)}{2t}} \frac{1}{[\theta_t(y)]^\alpha} (f(y) - f(x)) d\mu(y)$$

and again obtain bilinear forms $\Gamma(L_t^\alpha, f, f)$ and $\Gamma_2(L_t^\alpha, f, f)$. We consider the metric measure space $(\Sigma, \|\cdot\|, e^{-\rho} d\text{vol}_\Sigma)$ where $\Sigma^d \subset \mathbb{R}^N$ is an embedded submanifold, $\|\cdot\|$ is the ambient distance and ρ is a smooth function in Σ . We again take all the operators $L_t, \Gamma_t(L_t, \cdot, \cdot)$ and $\Gamma_2(L_t, \cdot, \cdot)$ with respect to the data of $(\Sigma, \|\cdot\|, e^{-\rho} d\text{vol}_\Sigma)$.

Theorem 1.9. *Let $\Sigma^d \subset \mathbb{R}^N$ be an embedded submanifold and consider the smooth metric measure space $(\Sigma, \|\cdot\|, e^{-\rho} d\text{vol}_\Sigma)$. Let $f \in C^5(\Sigma)$ such that $\|f\|_{C^5} \leq M$. There exists $C_4 = C_4(\Sigma, M, \rho)$ such that*

$$(1.16) \quad \sup_{\xi \in \Sigma} |\Gamma_2(L_t^\alpha, f, f)(\xi) - \Gamma_2(\Delta_{2(1-\alpha)\rho}, f, f)(\xi)| \leq C_4 t^{1/2}.$$

In particular, if the density is positive and smooth enough, we can still recover the Ricci tensor.

2. BIAS ERROR ESTIMATES

2.1. Bias for Submanifold of Euclidean Space. In this section we prove Theorem 1.6. The theorem will follow from Proposition 2.1 and Corollary 2.2 below. For simplicity we will assume that $(\Sigma, d\text{vol}_\Sigma)$ has unit volume. Recall the definitions (1.7), (1.8), (1.9), (1.10) and (1.11).

Proposition 2.1. *Suppose that Σ^d is a closed, embedded, unit volume submanifold of \mathbb{R}^N . For any x in Σ and for any functions f, h in $C^5(\Sigma)$ we have*

$$(2.1) \quad \frac{(2\pi t)^{d/2}}{\theta_t(x)} = 1 + tG_1(x) + t^{3/2}R_1(x),$$

$$(2.2) \quad \begin{aligned} \Gamma_t(f, h)(x) &= \langle \nabla f(x), \nabla h(x) \rangle + t^{1/2}G_2(x, J^2(f)(x), J^2(h)(x)) \\ &+ tG_3(x, J^3(f)(x), J^3(h)(x)) + t^{3/2}R_2(x, J^4(f)(x), J^4(h)(x)), \end{aligned}$$

$$(2.4) \quad L_t f(x) = \Delta_g f(x) + t^{1/2}G_4(x, J^3(f)(x)) + tG_5(x, J^4 f(x)) + t^{3/2}R_3(x, J^5 f(x)),$$

where each G_i is a locally defined function, which is smooth in its arguments, and $J^k(u)$ is a locally defined k -jet of the function u . Also, each R_i is a locally defined function of x which is bounded in terms of its arguments.

Corollary 2.2. *We have the following expansions*

$$(2.5) \quad L_t(\Gamma_t(f, f))(x) = \Delta_g \|\nabla f(x)\|_g^2 + t^{1/2} R_4(x, J^5(f)(x)),$$

$$(2.6) \quad \Gamma_t(L_t f, f)(x) = \langle \nabla \Delta_g f(x), \nabla f(x) \rangle + t^{1/2} R_5(x, J^5(f)(x)).$$

2.2. Proof of Proposition 2.1. Our first goal is to fix a local structure which we will use to define the quantities G_i and R_i and $J^k(u)$ that appear in Proposition 2.1. Choose a point $x \in \Sigma$, and an identification of tangent plane $T_x \Sigma$ with \mathbb{R}^n . Locally we may make a smooth choice of ordered orthonormal frame for nearby points in Σ so that at each point y there now is a fixed identification of the tangent plane. At each nearby point $y \in \Sigma$, we can represent Σ as the graph of a function U_y over the tangent plane $T_y \Sigma$. Each U_y will satisfy

$$(2.7) \quad U_y(0) = 0,$$

$$(2.8) \quad DU_y(0) = 0.$$

By our choice of identification, the functions U_y are well defined and for y near x and $z \in T_y \Sigma$ near 0, the function $(y, z) \mapsto U_y(z)$ has the same regularity as Σ . Fixing a point x , consider a function f on Σ . The function f is locally well defined as a function over the tangent plane, i.e.

$$(2.9) \quad f(y) = f(y, U_x(y)) \text{ for } y \in T_x \Sigma.$$

With the above identification we obtain coordinates on the tangent plane at x , and we may take derivatives of f in this new coordinate system to define the m -jet of f at the point x by

$$(2.10) \quad J^m f(x) = (f(x), Df(x), \dots, D^m f(x)).$$

More concretely, all derivatives in (2.10) are taken with respect to the variable y in (2.9). Since Σ is compact, there exists $\tau_0 > 0$ such that for every $y \in \Sigma$ we have

- (1) The function U_y is defined and smooth on $B_{\tau_0}(0) \subset T_y \Sigma$,
- (2) $B_{\mathbb{R}^N, \tau_0}(y) \cap \Sigma$ is contained in the graph of U_y over the ball $B_{\tau_0}(0) \subset T_y \Sigma$ where $B_{\mathbb{R}^N, \tau_0}(y)$ is the ball in \mathbb{R}^N centered at y with respect to the ambient distance.

We will use the following notation: given $y \in \Sigma$ and $\tau_0 > 0$ as above, we let

$$(2.11) \quad \Sigma_{y, \tau} = \Sigma \cap \{(z, U_y(z)), y \in B_\tau(0) \subset T_y \Sigma\},$$

in other words, Σ_{y, τ_0} is the part of Σ contained in the graph of U_y on $B_{\tau_0}(0) \subset T_y \Sigma$. Observe that with this notation, the statement in (2) above simply says that

$$(2.12) \quad B_{\mathbb{R}^N, \tau_0}(y) \cap \Sigma \subset \Sigma_{y, \tau_0}.$$

Observe that for any $f \in L^\infty(\Sigma)$ we have

$$(2.13) \quad \int_{\Sigma} f(y) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y) = \int_{\Sigma_{x, \tau_0}} f(y) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y)$$

$$(2.14) \quad + \int_{\Sigma \setminus \Sigma_{x, \tau_0}} f(y) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y),$$

and by (2)

$$(2.15) \quad \int_{\Sigma \setminus \Sigma_{x, \tau_0}(x)} f(y) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y) \leq \|f\|_{L^\infty(\Sigma)} e^{-\frac{\tau_0^2}{2t}}.$$

Note also, that for any polynomial $p(z)$, there is a constant C such that

$$(2.16) \quad \left| \int_{\mathbb{R}^d \setminus B_{\tau_0/\sqrt{t}}} e^{-\|z\|^2/2} p(z) dz \right| \leq C(p) e^{-\frac{\tau_0^2}{2t}}.$$

The volume form over $T_x \Sigma$ will be

$$(2.17) \quad \mu_x(z) dz = \sqrt{\det(\delta_{ij} + \langle D_i U_x(z), D_j U_x(z) \rangle)}.$$

If in (1.7) we choose our distance to be the ambient distance $\|\cdot\|$ in \mathbb{R}^N and the measure μ to be the volume measure in Σ , the density $\theta_t(x)$ takes the form

$$(2.18) \quad \theta_t(x) = \int_{\Sigma} e^{-\frac{\|x-y\|^2}{2t}} d\mu(y).$$

In the following, we will use $T_k f(x)(y)$ to denote the k -th order term in the Taylor expansion of f at x , in the variable y .

We now prove (2.1). Observe that

$$\begin{aligned} \theta_t(x) &= \int_{\Sigma \setminus \Sigma_{x, \tau_0}} e^{-\frac{\|x-z\|^2}{2t}} d\mu(z) \\ &= \int_{B_{\tau_0}} e^{-(\|z\|^2 + \|U_x(z)\|^2)/2t} \mu_x(z) dz \\ &= t^{n/2} \int_{B_{\tau_0/\sqrt{t}}} e^{-\|w\|^2/2} e^{-\|U_x(\sqrt{t}w)\|^2/2t} \mu_x(\sqrt{t}w) dw \\ &= t^{n/2} \int_{\mathbb{R}^d} e^{-\|w\|^2/2} e^{-\|U_x(\sqrt{t}w)\|^2/2t} \mu_x(\sqrt{t}w) dw \\ &\quad - t^{n/2} \int_{\mathbb{R}^d \setminus B_{\tau_0/\sqrt{t}}} e^{-\|w\|^2/2} e^{-\|U_x(\sqrt{t}w)\|^2/2t} \mu_x(\sqrt{t}w) dw. \end{aligned}$$

Now considering (2.17), (2.8) we have

$$(2.19) \quad \mu_x(\sqrt{t}w) = 1 + tT_2\mu_x(0)(w) + t^{3/2}R_2\mu_x(0, w),$$

$$(2.20) \quad e^{-\frac{\|U_x(\sqrt{t}w)\|^2}{2t}} = 1 + tT_4 \left[e^{-\|U_x(\sqrt{t}\cdot)\|^2/2t} \right] (0)(w) + t^{3/2}R_4 \left[e^{-\|U_x(\sqrt{t}\cdot)\|^2/2t} \right] (0, w).$$

Expanding, collecting lower order terms, integrating and absorbing the exponentially decaying terms into $t^{3/2}R_1(x, z)$ using (2.15) and (2.16) yields (2.1).

Next we prove (2.4). First compute

$$\int_{\Sigma} (f(y) - f(x)) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y).$$

$$\int_{B_{\tau_0}} (f(y) - f(x)) e^{-\frac{\|x-y\|^2}{2t}} \mu_x(y) dy = t^{d/2} \int_{B_{\tau_0/\sqrt{t}}} e^{-\frac{\|z\|^2}{2}} \left(f(\sqrt{t}z) - f(0) \right) \mu_x(\sqrt{t}z) dz$$

Now,

$$(2.21) \quad f(\sqrt{t}z) - f(0) = \sqrt{t}T_1f(z) + tT_2f(z) + t^{3/2}T_3f(z) + t^2T_4f(z) + t^{5/2}R_4(z)$$

and also recall (2.19). (2.20). Note that if A is a symmetric $d \times d$ matrix we have the identity

$$(2.22) \quad \int_{\mathbb{R}^d} z^T A z dz = (2\pi)^{d/2} \text{tr}(A),$$

where tr denotes Trace. From this it follows that

$$(2.23) \quad \int_{\mathbb{R}^d} e^{-\frac{\|z\|^2}{2}} T_2f(0)(z) dz = (2\pi)^{d/2} \text{tr}(T_2f(0)).$$

Again, expanding, collecting lower order terms, integrating odd and even terms, and absorbing the exponentially decaying terms via (2.15) and (2.16) yields

$$\begin{aligned} t^{-d/2} \int_{\Sigma} (f(y) - f(x)) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y) &= t(2\pi)^{d/2} \Delta_g f + t^{3/2} G_4(J^3 f(x)) \\ &\quad + t^2 G_5(J^4 f(x)) + t^{5/2} R_3(J^5 f(x)). \end{aligned}$$

Combining with (2.1) yields (2.4). A very similar calculation yields (2.2).

Proof of Corollary 2.2. Directly from (2.2)

$$(2.24) \quad L_t(\Gamma_t(f, f))(x) = L_t \left\{ \|\nabla f\|^2(x) + t^{1/2} G_2(x, J^2(f)(x)) + t G_3(x, J^3(f)(x)) \right\}$$

$$(2.25) \quad + t^{3/2} L_t R_2(x, J^4(f)(x))$$

This last term can be bounded directly by the definition of L_t :

$$\begin{aligned} t^{3/2} |L_t R(x)| &= t^{3/2} \left| \frac{1}{t} \frac{2}{\theta_t(x)} \int (R(y) - R(x)) e^{-\frac{\|x-y\|^2}{2t}} d\mu(y) \right| \\ &\leq \left| t^{1/2} \frac{2}{\theta_t(x)} 2 \|R\|_{L^\infty} \int e^{-\frac{\|x-y\|^2}{2t}} d\mu(y) \right| \\ &= 4t^{1/2} \|R\|_{L^\infty}. \end{aligned}$$

The first three terms are differentiable, so can be dealt with directly by (2.4), giving an expression involving $J^5(f)(x)$. The estimate (2.6) follows from a similar argument. The result follows by combining the above lemmata for the first term, and then directly bounding the second term. \square

2.3. Bias for Smooth Metric Measure Space with a Density. The bias estimate Theorem 1.6 for a metric measure space with density will follow from the following proposition whose proof is very similar to that of Proposition 2.1. Recall definitions (1.14) and (1.15) .

Proposition 2.3. *Let $f \in C^5$. We have the following expansions*

$$(2.26) \quad L_t^\alpha f(x) = \Delta_g f(x) + (1 - \alpha) \langle \nabla f(x), \nabla \rho(x) \rangle_g \\ + t^{1/2} G_1(x, J^3(f)) + t^{3/2} R_1(x, J^5(f))$$

$$(2.27) \quad \Gamma_t^\alpha(f, h)(x) = \langle \nabla f, \nabla h \rangle_g + t^{1/2} G_2(x, J^2(f), J^2(h)) + t^{3/2} R_2(x, J^4(f), J^4(h)).$$

Proof. Following the proof of Proposition 2.1 we have the following expansions

$$(2.28) \quad \theta_t(x) = (2\pi t)^{d/2} e^{-\rho(x)} (1 + tG_1(x, \rho) + t^{3/2} R_1(x, \rho)),$$

$$(2.29) \quad \theta_{t,\alpha}(x) = (2\pi t)^{(1-\alpha)d/2} e^{(\alpha-1)\rho(x)} (1 + tG_2(x, \rho) R_2(x, \rho)),$$

as $t \rightarrow 0$. Also, taking coordinates on the tangent plane of Σ at the point x and identifying x with 0 we have the expansion

$$(2.30) \quad \frac{d\mu_x(z)}{\theta_t(z)^\alpha} = e^{(\alpha-1)\rho(0)} (1 + (1 - \alpha) \langle D\rho(0), z \rangle + O(\|z\|^2)) dz,$$

which holds in a small neighborhood of 0. The rest of the proposition follows from a straightforward computation. \square

Corollary 2.4. *We have the following expansions*

$$L_t^\alpha(\Gamma_t^\alpha(f, h))(x) = \Delta \langle \nabla f, \nabla h \rangle_g(x) + (1 - \alpha) \langle \nabla \rho, \nabla \langle \nabla f, \nabla h \rangle_g \rangle_g(x) \\ + t^{1/2} R_3(x, J^5(f), J^5(h), J^5(\rho)), \\ \Gamma_t^\alpha(L_t^\alpha f, h)(x) = \langle \nabla \Delta_g f, \nabla h \rangle_g + (1 - \alpha) \langle \nabla \langle \nabla \rho, \nabla f \rangle_g, \nabla h \rangle_g \\ + t^{1/2} R_4(x, J^5(f), J^5(h), J^5(\rho)).$$

as $t \rightarrow 0$.

From Corollary 2.4 we obtain Theorem 1.9.

2.4. Convergence of Coarse Ricci to Actual Ricci on Smooth submanifolds.

We now prove Theorem 1.8:

Proof of Theorem 1.8. Our goal is to show that

$$|\text{Ric}(\gamma'(0), \gamma'(0)) - \text{RIC}_{L_t}(x, \gamma(s))| \leq C_1 t^{1/2} + C_2 s.$$

First, note that letting

$$f_s = f_{x, \gamma(s)}(\cdot) = \left\langle \frac{\gamma(s) - x}{|\gamma(s) - x|}, \cdot \right\rangle$$

and

$$f_0 = \langle \gamma'(0), \cdot \rangle$$

we have

(2.31)

$$\begin{aligned}
 |\text{Ric}_{L_t}(x, \gamma(s)) - \text{Ric}(\gamma'(0), \gamma'(0))| &= |\Gamma_2(L_t, f_s, f_s)(x) - \text{Ric}(\gamma'(0), \gamma'(0))| \\
 (2.32) \quad &= \left| \begin{aligned} &\Gamma_2(L_t, f_s, f_s)(x) - \Gamma_2(\Delta_g, f_s, f_s)(x) \\ &+ \Gamma_2(\Delta_g, f_s, f_s)(x) - \Gamma_2(\Delta_g, f_0, f_0)(x) \\ &+ \Gamma_2(\Delta_g, f_0, f_0)(x) - \text{Ric}(\gamma'(0), \gamma'(0)) \end{aligned} \right| \\
 (2.33) \quad &\leq R(J^5 f_s)t^{1/2} + C_7(\Sigma)s.
 \end{aligned}$$

Here we have used the following the facts:

First,

$$|\Gamma_2(L_t, f_s, f_s)(x) - \Gamma_2(\Delta_g, f_s, f_s)(x)| \leq R(x, J^5 f_s)t^{1/2}$$

by Corollary 2.2.

Second, a straightforward computation yields that for any two functions f_0, f_s

(2.34)

$$\begin{aligned}
 |\Gamma_2(\Delta_g, f_s, f_s)(x) - \Gamma_2(\Delta_g, f_0, f_0)(x)| &\leq (\|f_0\|_{C^2} + \|f_s\|_{C^2}) \|f_s - f_0\|_{C^2} \\
 (2.35) \quad &+ \|f_0\|_{C^3} \|f_s - f_0\|_{C^1} + \|f_s\|_{C^1} \|f_s - f_0\|_{C^3}.
 \end{aligned}$$

Since the functions f_0, f_s are ambient linear functions restricted to a submanifold, the higher derivatives are well-controlled. The derivatives of the difference are controlled as follows

$$\begin{aligned}
 \|f_s - f_0\|_{C^3} &= \left\| \left\langle \frac{\gamma(s) - x}{\|\gamma(s) - x\|} - \gamma'(0), \cdot \right\rangle \right\|_{C^3} \\
 &\leq \left\| \frac{\gamma(s) - x}{\|\gamma(s) - x\|} - \gamma'(0) \right\| \|z\|_{C^3}
 \end{aligned}$$

where $\|z\|_{C^3}$ is the norm of the derivatives of the coordinate functions, which is also controlled by the geometry of Σ . Certainly, for any unit speed curve with bounded curvature we have

$$\left\| \frac{\gamma(s) - x}{\|\gamma(s) - x\|} - \gamma'(0) \right\| \leq \kappa s.$$

The curvature of any geodesic inside Σ is controlled by the geometry of Σ . Finally, because

$$\nabla f_0 = \gamma'(0)$$

we have by the Bochner formula

$$(2.36) \quad \Gamma_2(\Delta_g, f_0, f_0)(x) - \text{Ric}(\gamma'(0), \gamma'(0)) = \|\nabla^2 f_0\|^2.$$

Using the tangent plane as coordinates at a point, it is easy to compute that the Hessian of any coordinate function vanishes at the origin. The vector $\gamma'(0)$ is in the tangent space, so we conclude that (2.36) vanishes.

□

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